OPTIMAL REAL-TIME ACTIVATED SLUDGE REGULATION

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INTRODUCTION

An application of optimal control techniques in regulating a conventional activated sludge process (Figure 1) is presented. In this process, organics in the influent wastewater (substrate) serve as energy source for the aerobic growth of microorganisms (biomass or activated sludge) in the biological reactor. The resulting mixed liquor is purified (clarification) by settling of the microbial flocs in a following tank (settler). The thickened sludge is recycled to the biological reactor to sustain the biomass amount. To maintain a constant amount of biomass in the system, excess biomass is regularly removed (wastage). The process can be regulated by varying certain inputs such as the wastewater feed point, sludge recycle and wastage rates, aeration rate, and on-line sludge storage and resupply rates. The scope of this paper is to present an application of an optimal control method to a detailed activated sludge model, consisting of a multicomponent biological reactor and a dynamic multilayer settler. A real-world implementation for the Yellow River/ Sweetwater Creek wastewater treatment plant in Gwinnet county is presently being conducted.

SYSTEM AND CONTROL MODELS

The employed biological model is a reduced order form of the International Association on Water Pollution Research and Control (IAWPRC) group model of single-sludge processes (Henze et al., 1987). This model is presented in matrix format in Table 1. The components modelled are active biomass (X_B), particulate products of biomass decay (X_P), slowly biodegradable (particulate) substrate (X_S), inert particulates (X_I), and readily biodegradable (soluble) substrate (S_S), all expressed as Chemical Oxygen Demand (COD). The processes modelled are aerobic growth of heterotrophs at the expense of substrate, decay of heterotrophs, and extracellular "hydrolysis" of particulate substrate to soluble substrate. Typical values of the stoichiometric and kinetic parameters are given in Henze et al. (1987). From Table 1, the

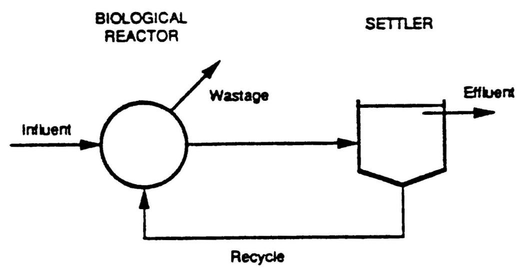

Figure 1. The Conventional Activated Sludge Process.

apparent reaction rate for component i (concentration difference per unit time), can be obtained from the stoichiometric coefficients ν_{ij} and the process rates ρ_j according to

$$r_i = \sum_j \nu_{ij} \rho_j \tag{1}$$

The apparent reaction rates can then be incorporated in mass balance equations for each component in the biological reactor as follows:

$$\frac{dC}{dt} = \frac{\sum_i Q_i C_i - \sum_j Q_j C}{V} + r_C \tag{2}$$

where C is the considered concentration, Q_i the ith input flowrate, C_i concentration of component in stream i, Q_j jth output flowrate, V reactor volume, r_C component's C apparent reaction rate.

The settler model is based on the flux theory assumption that superposition of bulk and settling solids fluxes yields the total solids flux in a settler. This approach is applied under dynamic settler operating conditions. The Vesilind exponential empirical relationship (Vesilind, 1968) is used to predict the settling velocity as a function of the total particulates concentration. The settler is discretized to a series of completely-mixed layers reducing the partial

Table 1: Activated Sludge Kinetics and Stoichiometry

	$\rightarrow i$	1	2	3	4	5	
Components		X_B	X_P	X_S	X_I	S_S	
$j \downarrow$	**Processes**	**Stoichiometric coefficients, ν_{ij}**					**Rates, ρ_j, $ML^{-3}T^{-1}$**
1	Growth	1				$-\frac{1}{Y}$	$\hat{\mu}\frac{S_S}{K_S+S_S}\frac{S_O}{K_O+S_O}X_B$
2	Decay	-1	f	$1-f$			bX_B
3	Hydrolysis			-1		1	$K_H\frac{X_S}{K_X+(X_S/X_B)}\frac{S_O}{K_O+S_O}$

differential equation for the particulates continuity to a system of ordinary differential equations for each layer. To comply with the idea of vertically non-dispersive solids mass, the settling flux in any layer is not allowed to exceed the settling flux of the layer below. To avoid discontinuities introduced by the above-described flux constraint between adjacent settler layers, the transition of flux values is smoothened by an appropriate continuous switching function.

Assembling the mass balance equations for concentrations of the components around the system in a single vector, gives rise to the following (state-space) activated sludge model:

$$\frac{dx}{dt} = f(x(t),u(t),w(t),a), \quad x(0) = 0 \qquad (3)$$

where x(t) is the state vector including all component concentrations throughout the system (five variables per biological reactor and each settler layer), x(0) a known initial state vector, u(t) control vector including all controllable process variables (e.g. the wastage and recycle rates), w(t) vector of process inputs (wastewater components load), a vector of all model parameters (e.g. kinetic and stoichiometric parameters), f( ) vector function whose elements are the right-hand side expressions of the mass balance equations.

A primary objective of the activated sludge operation is to maintain the effluent organics concentration below certain regulatory limits. Another operational objective is to minimize the energy required for pumping the recycle and wastage flows.

A performance index consistent with these objectives is as follows:

$$J = \frac{1}{2}\int_{t_0}^{t_T}\left[\delta x^T(t) Q \delta x(t) + \delta u^T(t) R \delta u(t)\right] dt \qquad (4)$$

where $\delta x(t) = x(t) - x^*(t)$, and $\delta u(t) = u(t) - u^*(t)$ are perturbations of the state and control vectors from desired target values (asterisked) at time t. Q(t) and R(t) are symmetric, positive semi-definite and positive definite coefficient matrices respectively (superscript 'T' denotes transposition). Minimization of the above performance index with respect to the control vectors $\{u(t), t \in [t_0, t_T]\}$ will produce state and control trajectories in the vicinity of the respective targets. The target state vectors can be taken as the steady-state response to average inputs with control variables equal to their target values.

Matrices Q(t) and R(t) are weighing coefficients whose relative magnitudes determine which state or control terms have minimization priority in Equation 4. Furthermore, the relative magnitudes of the matrix elements govern the minimization priority for the different components of the given vector.

In the above formulation, the control variables are the recycle and wastage rates. The previous optimization problem is characterized by high dimensionality and system model nonlinearity. The solution is obtained by a Newton-type trajectory iteration control method (Kabouris and Georgakakos, 1990). In the case study section, this approach is compared with the commonly proposed recycle ratio control strategy.

CASE STUDY

The previous methodology is applied to the system shown in Figure 1 where the volume of the biological reactor is 250 m^3 and the settler is divided in 4 layers. The process inputs are presented in the first graph of Figure 2 (Metclf and Eddy, 1979). The sludge recycle rate and the incoming flowrate are kept at a ratio equal to one as seen in the second graph of Figure 2. The associated concentration sequences for the biological reactor and each settler layer are presented on Figure 3. The resulting biological reactor soluble organics sample standard deviation, SD, is equal to 0.79 g COD/m^3. The second test concerns the application of the control method presented earlier. The discretization interval used was 1 minute, and the control horizon was 1 day (1440 time steps). This formulation involves 2880 optimization variables. The weight of the control variables was calibrated to limit the control variations within a reasonable region. The target wastage rate was chosen by a trial-and-error procedure to yield the same daily wasted active biomass with the previous experiment. The resulting control variable trajectories are presented in the third graph of Figure 2 and the associated concentration trajectories are shown in Figure 4. The soluble organics deviation is now reduced to SD=0.71 g COD/m^3 which represents a 10% reduction with respect to the ratio control strategy. The major reduction of the soluble substrate variation results from the diurnal wastage flow variation. The controller initially reduces the wastage rate to accumulate biomass in

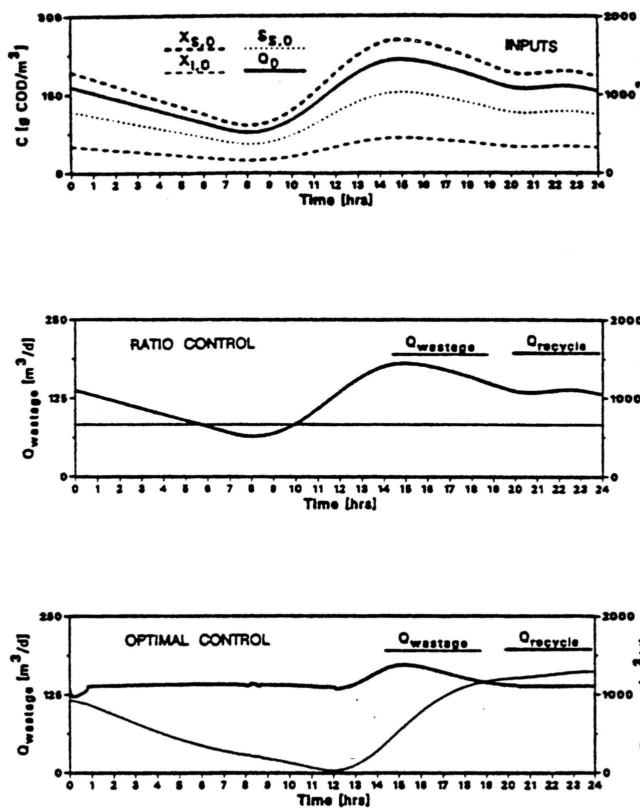

Figure 2: Input and Control Variable Trajectories

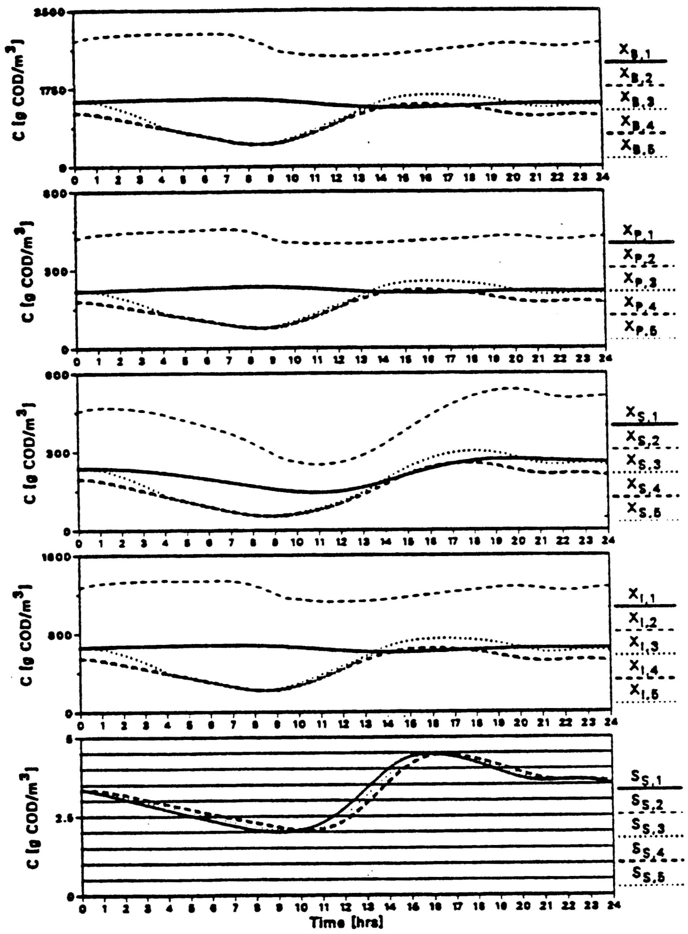

Figure 3: Activ. Sludge Responce to Ratio Recycle Control

the biological reactor. This happens despite the initial reduction of the input substrate supply rate, in anticipation of the subsequent substrate load arrival. The sludge recycle rate control variable is reduced during the first hour. From there on, it follows its target value except during high plant loading periods where it increases to assist in the transfer of active biomass in the biological reactor according to the ratio control principle. Compared to the the ratio control strategy, the controlled experiment is more effective since the recycled solids concentration is maintained higher at the critical period of increased plant loading. To further enhance the capacity of highly concentrated return solids, decoupling of the biological reactor and settler operation is necessary. This can be achieved by introducing a sludge storage tank after the settler and before the biological reactor, with controllable inflow and outflow.

In a real-time implementation of this control approach, critical factors are the uncertainty in the future process inputs and the time-varying nature of the process model parameters. These factors necessitate the development of a stochastic control framework in which the process is observable through a set of measurements. These measurements can help fine-tune the mathematical process model to the actual system conditions. This information, along with statistical process input forecasts, can be utilized by a controller designed to regulate the process so as to satisfy the system objectives. The development of such an integrated control scheme is currently under investigation.

In the above experiments the control algorithm practically converged in three to four iterations, using for each iteration approximately 380 CPU seconds on a CDC CYBER 990 mainframe computer.

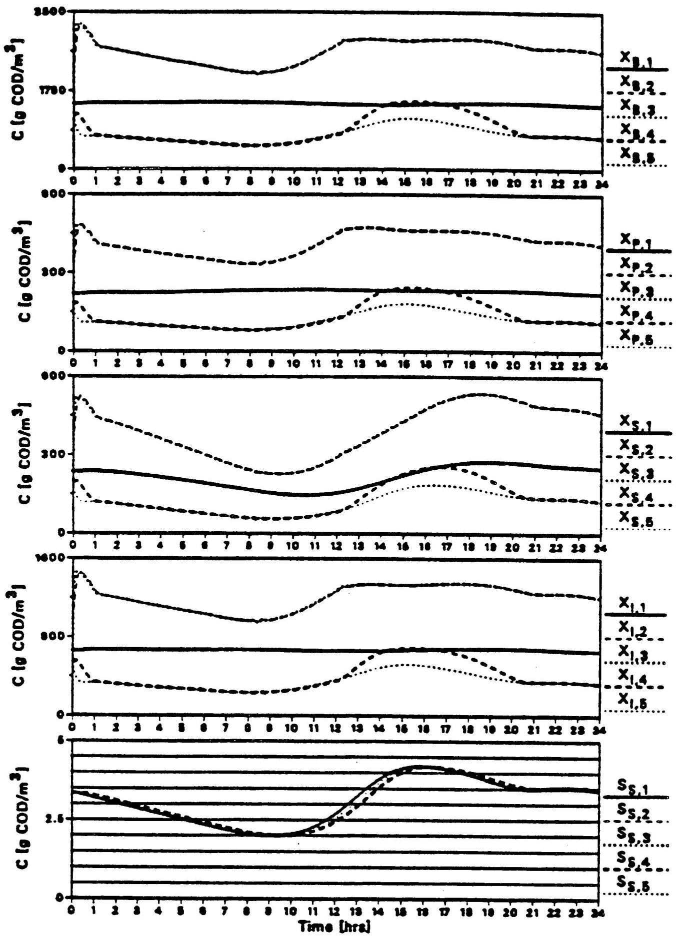

Figure 4: Controlled Activated Sludge Responce

CONCLUSIONS

In summary, (1) the suggested optimal control technique can handle the process nonlinearity and high dimensionality; (2) the commonly adopted recycle ratio control practice is practically ineffective for reducing effluent organics variability; and (3) combined sludge recycle and wastage regulation reduces the variability of effluent organics to 90% of the recycle ratio strategy value.

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